



Ma, A., Nassehi, A., & Snider, C. (2019). Anarchic Manufacturing. *International Journal of Production Research*, 57(8), 2514-2530.
<https://doi.org/10.1080/00207543.2018.1521534>

Peer reviewed version

Link to published version (if available):
[10.1080/00207543.2018.1521534](https://doi.org/10.1080/00207543.2018.1521534)

[Link to publication record in Explore Bristol Research](#)
PDF-document

This is the author accepted manuscript (AAM). The final published version (version of record) is available online via Taylor & Francis at <https://www.tandfonline.com/doi/full/10.1080/00207543.2018.1521534> . Please refer to any applicable terms of use of the publisher.

University of Bristol - Explore Bristol Research

General rights

This document is made available in accordance with publisher policies. Please cite only the published version using the reference above. Full terms of use are available:
<http://www.bristol.ac.uk/red/research-policy/pure/user-guides/ebr-terms/>

Anarchic Manufacturing

Andrew Ma, Aydin Nassehi and Chris Snider

Design & Manufacture Futures Laboratory, University of Bristol, Bristol, BS8 1TR, UK

ABSTRACT

This paper introduces anarchic manufacturing, an extremely distributed planning and control philosophy as the methodology for planning and controlling future smart factories. Anarchic manufacturing delegates decision making authority and autonomy to the lowest level of entities in system elements with no centralised control or oversight. It is often postulated that traditional hierarchical structures may not be well suited to manage the state-of-the-art hyper-connected smart factories due to their reliance on communication between management layers. Distributed systems, on the other hand, are commonly perceived to be inherently more flexible, robust and adaptable than hierarchical systems due to their structure. This paper characterises distributed systems by evaluating the relative flexibility of a representative hierarchical system against an anarchic system in a job shop scenario. Multi agent based simulation is used to model both hierarchical and anarchic systems, which are tested for flexibility following the Taguchi method and compared against Tailard's benchmark job shop problems for overall performance. The results show that the anarchic system performs as well as the hierarchical system when subjected to unforeseen disruption, refuting the argument that hierarchical systems are too rigid and distributed systems are inherently more flexible. However, anarchic manufacturing systems, which show adaptability and self-optimising traits, provide a platform to potentially enable the emerging digital manufacturing paradigm through the free market structure especially when bandwidth for communications is limited.

KEYWORDS

Distributed systems, Multi agent systems, Simulation, Flexibility

1. Introduction

Global manufacturing is moving from mass production to mass customisation, driven by a demand for increased product customisation and personalisation (Hu 2013). The volatile change in customer demands has driven manufacturers to become more robust, dynamic and responsive, using technology to achieve these attributes (Mourtzis and Doukas 2014). Modern manufacturers have to frequently adapt to dynamic and unpredictable environments, particularly for job shops and flow shops (Scholz-Reiter, Rekersbrink, and Görges 2010). To counter volatile environments, manufacturers employ flexible operations as a strategic and competitive priority (Narasimhan, Talluri, and Das 2004; Ivanov, Das, and Choi 2018), often using smart manufacturing technologies (Kusiak 2018).

One of the most difficult problems manufactures face in volatile environments, with high product turnover and constant change is scheduling operations. Scheduling is a complex problem, and becoming increasingly important with the uptake in automation

Andrew Ma. Email: andrew.ma@bristol.ac.uk

Aydin Nassehi. Email: aydin.nassehi@bristol.ac.uk

Chris Snider. Email: chris.snider@bristol.ac.uk

and want of flexibility in manufacturing (Scholz-Reiter, Rekersbrink, and Görges 2010). Traditionally, hierarchical scheduling methods are used to solve for optimal solutions, these are best designed for and operate in static well-defined problems but are too inflexible to effectively cope with real-time disruptions.

Scholz-Reiter, Rekersbrink, and Görges (2010) found in complex scenarios a central strategy tries to satisfy all constraints at once, becoming inflexible to increasing volatility or complexity. Multi-agent heterarchical distributed systems, underpinned by the emergent synthesis concept, have been shown to increase robustness and flexibility (Ouelhadj and Petrovic 2009). Emergent synthesis methods have been identified to best solve problems with incomplete knowledge areas, where a global emergent direction arises from multiple elements pursuing individual interests and goals (Ueda et al. 2001).

Scholz-Reiter, Rekersbrink, and Görges (2010) state that the next research steps should evaluate heterarchical distributed systems in general problem formulations, such as job shop problems, for robustness against unforeseen disruptions. This paper aims to explore purely distributed systems, with no central control or oversight. “Anarchy” in manufacturing is defined as a heterarchical distributed structure where decision making authority and autonomy is at the lowest level, between system elements. This Anarchic Manufacturing System is then compared against a simple hierarchical system and tested against Taillard (1993) benchmark job shop scheduling problems for effectiveness, and a set of job shop scenarios with unforeseen disruptions to evaluate robustness following a Taguchi method to evaluate multiple parameters (Clemson et al. 1995). The later set of experiments tests the relative flexibility of the anarchic to hierarchical systems; distributed systems have been assumed to be inherently flexible (Shen and Norrie 1999).

This paper, an extension of Nassehi and Ma (2017) ‘A prelude to Anarchic Manufacturing’, first covers the background for anarchic distributed manufacturing systems with an applicable definition of flexibility. It then demonstrates how the anarchic and hierarchical systems were modelled using agent based modelling, including relevant agent interaction mechanisms. The experimental framework is then outlined for both Taillard’s job shop problems and flexibility tests following the Taguchi method. The results for both of these sets of experiments are displayed and discussed, before concluding.

2. Background

2.1. *Manufacturing Paradigms*

Recent manufacturing paradigms, Flexible Manufacturing Systems (FMS), Reconfigurable Manufacturing Systems (RMS) and most recently Cloud Based Manufacturing (CBM), all aim to improve flexibility (Jovane, Koren, and Boer 2003; Bi et al. 2008; Liu et al. 2018). FMS utilises mechanisation and low level automation to improve flexibility and product variety (Jovane, Koren, and Boer 2003); however, high software complexity, investment and maintenance cost with low reconfigurability have limited FMS takeup (Mehrabi, Ulsoy, and Koren 2000).

RMS utilises reconfigurable and modular elements to significantly reduce ramp-up time whilst maintaining reliability (Koren, Wang, and Gu 2017). Koren et al. (1999) compares dedicated manufacturing lines, FMS and RMS show their relative limitations and benefits, additionally the enabling technologies and improvements for

RMS are discussed. The most significant of these is the coupling of open-architecture reconfigurable controllers. For the flexibility and responsiveness benefits of RMS to be realised, improvements in interrelated technologies and design for reconfigurability are required. Job shops are typically highly flexible small manufacturers of one-offs or small batches, not necessarily constrained to individual MTs.

CBM is a service and customer orientated manufacturing model, where customers can access on-demand shared resources, these can be diversified across multiple entities. By utilising distributed resources, temporary and reconfigurable production systems are created; envisioned to improve efficiency and resource utilisation (Wu et al. 2013).

2.2. *Scheduling and control*

Allwood et al. (2015) observed increasing a manufacturers product variety led to a decrease in productivity and a significant increase in production time due to conflicting demands. The predominate method to manage product mix complexity has been to design in product families or platforms. However, these current simplification methodologies have their limitations, and do not address the increasing trend in volatility of market dynamics. Scholz-Reiter and Freitag (2007) states conventional structures and methodologies cannot handle dynamic environments, including unpredictable events and disturbances, in a satisfactory manner.

There is a shift from centrally controlled hierarchical systems to decentralised intelligent control of the systems elements (Scholz-Reiter, Windt, and Freitag 2004). Distributed intelligent systems, utilising a flat heterarchical structure, have decision making autonomy (Hülsmann and Windt 2007). Local interactions between intelligent agents within a society aim to solve a given problem (Kádár and Monostori 2001), whilst exhibiting flexible autonomous behaviour with social ability, reactivity and pro-activeness (Wooldridge et al. 1995).

Scholz-Reiter, Rekersbrink, and Görges (2010) compares autonomous control methods, which enable system elements to make decisions, against a centralised scheduling heuristic in a flexible flow-shop scenario. Centralised scheduling performed better regardless of system complexity, however the autonomous system was favourable for multi-stage and dynamic scenarios. It was concluded that centralised methods aim to satisfy all constraints simultaneously, this proved to be too restrictive in evolving environments; rather autonomous and distributed methods would divide the problem and successively solve these sub-problems.

Production scheduling is traditionally done by a human scheduler who centrally plans considering a number of factors, including fulfilling orders, demands and restrictions, reducing inventory, etc. (Berglund and Karlton 2007). Centralised strategies are typically poor at dealing with dynamic and changing environments, there are a number of centralised dynamic scheduling methods researched which Ouelhadj and Petrovic (2009) categorises into; heuristics, meta-heuristics and other artificial intelligence methods. This paper uses a heuristic (dispatch rule) with triggered rescheduling as a comparable centralised scheduling system.

2.3. *Control architectures*

There are varying degrees of centralised control, Figure 1 illustrates the decision making structure for centralised to anarchic structures. This paper evaluates the anarchic

manufacturing system, a flat autonomous intelligent multi-agent system, against job shop scenarios and characterises any inherent flexibility relative to centralised scheduling systems. The two extreme systems were chosen to evaluate inherent traits.

Hierarchical architectures are those that have a layered management structure, with decreasing authority and autonomy. These hierarchical and centralised structures typically have a master / slave relationship, and traditionally use structure to handle complexity (Heragu et al. 2002). They are the predominate management structure in industry, particularly for non-autonomous human-centred shop-floors, which often use simple dispatch heuristics; for example a job shop queueing estimate heuristic (Chang 1997). There has been extensive research into advanced centralised methods, for example advanced search heuristics, to obtain optimal solutions in static environments. Centralised methods are criticised for being too rigid and very poor at reacting to dynamic situations (Scholz-Reiter, Rekersbrink, and Görges 2010). Recent related works in centralised systems cover advanced search algorithms for similar scenarios; Shamshirband et al. investigates a genetic-based open-shop scheduling on considering machine maintenance (Shamshirband et al. 2015), additionally Hosseinabadi et al. uses a gravitational emulation local search algorithm for multi-objective dynamic job shop scheduling (Hosseinabadi et al. 2015). For this study a simple (First In First Out) FIFO heuristic is used to compare hierarchical systems relative to anarchic, this is sufficient to evaluate inherent traits of the two system types.

Distributed systems have at least some degree of low level decision making, there are various system currently researched for distributed scheduling and control and underpinned by the concept of emergent synthesis. Distributed systems, by contrast to hierarchical and centralised structures, have a degree of decision making freedom at the lowest levels of the system. Due to reported rigidity and lack of fault tolerance of hierarchical systems, there has been a significant rise in research of decentralised production control systems (Meissner, Ilse, and Aurich 2017). Semi-heterarchical systems, also known as hybrid systems, such as Fractal Manufacturing Systems (Ryu and Jung 2003) and Holonic systems (Heragu et al. 2002), aim to benefit from both hierarchical and distributed attributes. Low level decision making is autonomous within certain bounds, which are defined hierarchically. The hierarchical structure aims to provide stability and reduce complexity whilst enabling emergent behaviour and outcomes from low level autonomy (Ryu and Jung 2003). Heterarchical mediator architectures such as MetaMorph II, a Distributed Artificial Intelligence (DAI) system (Shen, Weiming, Maturana, Francisco & Norrie 2000), allow autonomous behaviour but uses centralised agents for special purposes, such as conflict resolution, macro optimisation and brokering.

Fully heterarchical systems, including anarchic manufacturing systems, have no centralised control or oversight; related projects in this field are DAI, Distributed Multiple Agent Systems (DMAS) and Biological Manufacturing Systems (BMS) (Pendharkar 1999; Shen and Norrie 1999; Ueda et al. 2001). Distributed systems are underpinned by the concept of emergent synthesis where individual elements pursue their own objectives without any particularly defined macro objective, to solve unforeseen or unquantifiable problems (Ueda et al. 2001). DAI and DMAS use artificial intelligence in agents to represent a system element, enabling autonomous behaviour and interaction with other agents and its environment. BMS takes inspiration from biomimetic design, Ueda uses field attraction and an ant colony pheromone mechanism in Ueda, Vaario, and Ohkura (1997); Ueda, Kito, and Fujii (2006), whilst applying an Evolutionary Artificial Neural Network for agent decision making in Ueda, Fujii, and Inoue (2007). This draws on the rapidly growing area of Machine Learning within Artificial

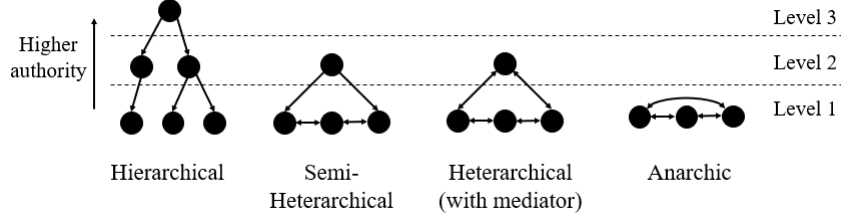


Figure 1. Centralisation of structures

Intelligence.

Anarchic Manufacturing systems, introduced in this paper, is a fully heterarchical structure using a free market architecture. Free market principles are at the centre of the Anarchic system’s design principles, aiming to benefit from traits of self-organisation, adaptability and efficiency. At a low level the inter-agent negotiation mechanisms are an extension of the contract net protocol and Kádár’s contract net protocol with cost factor adaptation (Kádár and Monostori 2001). Intelligence allows agents to adjust their behaviour according to their environment and interaction with other agents. A free market architecture for distributed systems takes advantage of the flexibility and high adaptability traits, thus gaining a highly productive society (Dias and Stentz 2000). The free market additionally benefits from very well understood economic theory and practice; creating a platform that can be easily developed further. A competitive structure between similar agents was used, as agents within a particular type were homogeneous and therefore in competition with each other, whilst heterogeneous agent types cooperated (Pendharkar 2012).

2.4. *Defining flexibility*

Sethi and Sethi (1990) states that complexity and multidimensionality are the only clear aspect of manufacturing flexibility. Cantamessa (1997) describes manufacturing flexibility as; the ability in the short term for systems to adapt to changes in product mix, process plans and machine status, and in the medium and long term the ability to sustain changes in demand, product characteristics, quantity and quality. Golden and Powell (2000) define four dimensions of flexibility; temporal, range, intention and focus.

Only temporal and range dimensions are appropriate to the bounded and closed manufacturing system modelled, without external interaction, focusing on short term operational problems. Intention and focus are beyond the scope of this study, as they evaluate the high level and strategic flexibility. Temporal and range dimensions address the ability to handle and adapt to foreseen and unforeseen changes in the environment. Efficiency and responsiveness measure the temporal dimension, and robustness and versatility measures range (Golden and Powell 2000). These appropriate qualitative metrics are measured quantitatively and defined in Section 6.2.

Golden and Powell (2000) state, within the temporal dimension, an efficient system can accommodate change with minimal reduction in performance; thereby maintaining efficiency whilst responding to change. Responsive systems can adapt to change in a suitable period of time. In the range dimension, versatility measures the range of circumstances and activities that a system has planned for, responding to foreseeable changes in environment; this was unsuitable to investigate as the tested systems need

to be directly comparable for the jobs processed. Robustness measures the system's ability to react to unforeseen or unpredictable changes in the environment (Golden and Powell 2000); this was not tested at a high strategic level but at a low operational level.

2.5. Study aims

This study investigates a distributed system against a centralised hierarchical system, testing for any inherent relative flexibility; a general problem was used where fundamental differences would be observable. It is commonly thought that decentralised distributed systems have an inherent flexibility and that hierarchical systems are too rigid for modern manufacturing (Shen et al. 2006). The distributed system selected is an anarchic manufacturing system at the extreme end of decentralisation. The testing methodology, following the Taguchi method, varies a large number of parameters associated with unforeseen disruption and the anarchic system's structure, including its free market design. Relative flexibility was analysed to compare the two systems.

To test the two selected manufacturing systems for inherent flexibility, a general problem was formed associated with job shop scheduling. A periodic batch arrival of jobs, requiring two operations of a predefined randomly allocated duration and capability, are processed by machines, with overlapping capabilities and susceptibility to failure. Relative flexibility was characterised through observing the systems' response to unforeseen disruption. The high and random variability of operations mimics the likely challenges faced in Industry 4.0; as demand for mass customisation and rapid lead times can lead to volatile environments for manufacturers.

2.6. Modelling platform

A manufacturing system where elements have decision-making intelligence and autonomy, enabling them to coordinate themselves through interaction, can be modelled using agent-based models (Cantamessa 1997). Individual agent behaviour, decision making and communication, using discrete-event processes and logic, enables agent interactions. Bigus and Bigus (2001) states a general programming language, such as Java, can model intelligent agents; however, the multi-method software platform AnyLogic 7 eliminates the need to create agents from scratch, the platform can combine system dynamics, multi-agent and discrete-event modelling (Borshchev 2013). AnyLogic processes and commands have been adjusted to counter multi-agent modelling issues to obtain the expected functionality, these include: synchronous vs asynchronous communication, deadlocks, simultaneous event firing issues.

3. Agent based modelling of an anarchic manufacturing system

3.1. Anarchic model

The Anarchic Manufacturing system's design principles stem from free markets and use a permutation of the contract net protocol, this is most suitably modelled using agent based models. See Section 2.3 for relevant literature for Anarchic systems. Agent based models utilise a population of interacting and individually addressable agents of different types; each agent type has predetermined decision-making logic and behaviour. Agent types represent different system elements, for example; jobs, MTs,

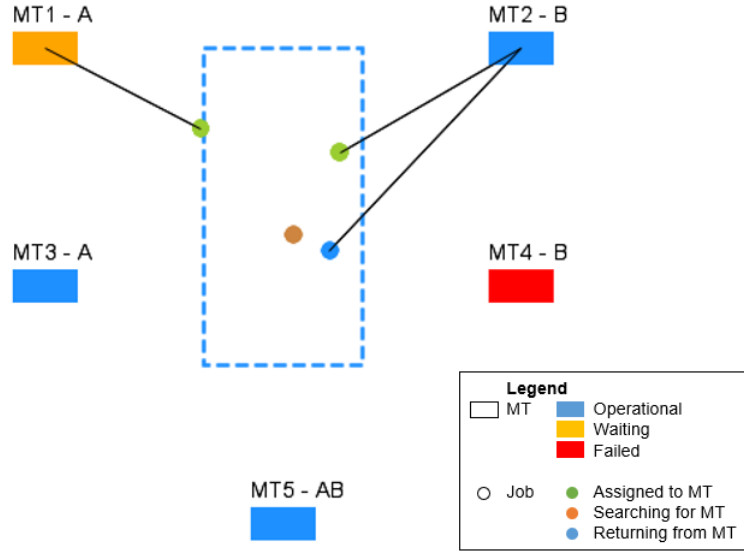


Figure 2. Agent based manufacturing system

operators or transporters. Agents use discrete event state charts to model behaviour, actions and decision making; agents can communicate via messaging, as well as observe and change each others parameters. Advanced agent based models can simulate complex scenarios and have non-deterministic behaviour. Figure 2 is a graphical representation of two agents, Jobs (J) and MTs (M); Jobs are represented by circles and MTs by rectangular. Agents can change colour and size according to their status, and a solid line between agents signals communicating agents.

Agent based modelling uses asynchronous messaging between agents, meaning that the order of sequentially sent messages is not necessarily preserved on the receiving end. To combat this synchronisation issue in agent based modelling an Operation handler (O) is used; avoiding simultaneous event firing issues and clashes, the Operation handler has no functional use with respect to scheduling. The anarchic manufacturing S is represented by the ternary (J, M, O).

Agent based models created in AnyLogic uses statecharts to model behaviour, transitions between statecharts and nomenclature are shown in Figure 3. State transitions occur within agents, message receipt and agent arrival transitions are triggered by other agents, timeout, condition and decision transitions are evaluated by the agent. The return to historic point returns an agent to its previous point and action within a state.

3.2. Job agents

Job agents need to complete a predetermined sequence of operations to exit the system. For the distributed system, jobs only plan the next operation rather than determining a route through the whole manufacturing system. Assuming that planning is concerned with r Jobs, the Job set is composed as:

$$J = \{j_1, j_2, \dots, j_r\} \quad (1)$$

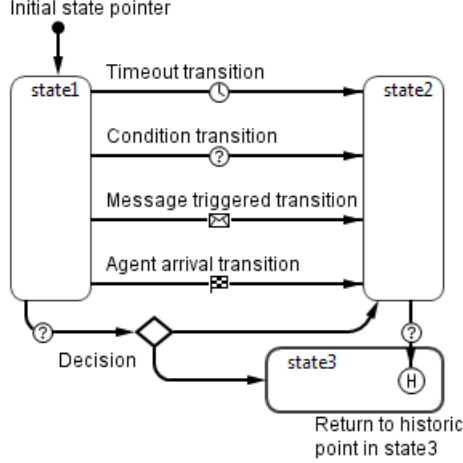


Figure 3. Statechart nomenclature

With j_1 representing job i . To complete operations, Jobs are given a budget to spend on consuming services; they are also instructed to spend so that they have sufficient budget to complete all their future operations. In the proposed agent based model, jobs have multiple budget currencies; operational, emissions and environmental; see Section 4.1 for an explanation of multiple currencies. The cost of an operation is associated with both operational and emissions budget. Time in system is associated with environmental budget, which is continuously deducted whilst the Job is in the manufacturing system; this increases the job's appetite for risk which acts as a lean mechanism.

To determine the available budget to spend on a given operation, the Job accounts for both its remaining budget and future operations; to ensure its ability to complete all operations. $\gamma_{ij}(t)$ denotes the remaining budget in budget category j for job i at time t . $\psi_i(t)$ denotes the remaining number of operations for Job i at time t . So, if $\lambda_{ij}(t)$ is the allocated budget for an operation for job i in budget category j at time t , the Job allocates remaining budget equally to all remaining operations, following the equation:

$$\lambda_{ij}(t) = \frac{\gamma_{ij}(t)}{\psi_i(t)} \quad (2)$$

Job agent behaviour is governed by the state chart shown in Figure 4. For a Job's next operation, of capability C_i , it tries to find a capable MT, of capabilities C_k , within reasonable cost for its allocated budget for that operation through a tendering and bidding process; given that the MT is close enough to communicate with. There is a limited communication range for Jobs connecting to other agents; this communication range for Job i is denoted by ϕ_i and the distance between the Job i to MT k at time t is denoted by $D_{ik}(t)$. The set of MTs who qualify to tender is evaluated as:

$$M_{iBid} = \{M_k | C_i \in C_k \vee D_{ik}(t) < \phi_i\} \quad (3)$$

MTs tender and bidding is evaluated over a certain number of bidding rounds, to

see whether the lowest cost MT of M_{iBid} is below the Job's threshold. The Job's cost threshold for each budget in bidding round n , $\alpha_{ijn}(t)$, is increased by the factor $\rho_i(t)$ between each bidding round; $\rho_i(t)$ is the Jobs appetite for risk at time t . The initial thresholds for each currency is evaluated by:

$$\alpha_{ijn}(t) = 0.9\lambda_{ij}(t) \quad (4)$$

All subsequent bid rounds, $n + 1$, cost thresholds are evaluated by:

$$\alpha_{ijn+1}(t) = \rho_i(t) \cdot \alpha_{ijn}(t) \quad (5)$$

Where the risk factor ρ_i is a function of time, budget remaining and operations remaining denoted as:

$$\rho_i(t) = f(t, \gamma_i, \psi_i) \quad (6)$$

Appetite for risk and the subsequent willingness to spend more contributes to the free market mechanism, where price rises as demand increases against a fixed supply. Additionally, the concept of risk highlights the agent's intelligence and changing behaviour in response to it's dynamic environment. If successfully allocated to a MT, the Job will join the queue for the MT and on completing the operation rejoin the waiting area, if unsuccessful the Job will move elsewhere to try to find a suitable MT. On completing all operations the Job will exit the system. Whilst a Job is waiting and unable to find a suitable MT, some budgets are regularly increased and the Job can trade with other Jobs; see Section 4.2 for an explanation of inter-job trading. Within a free market a Job with insufficient funds would not be processed at all, a regular budget increase negates this for manufacturing, as all Jobs must be processed eventually even those with an initial low priority.

3.3. Machine Tool agents

MT agents are service providers on a chargeable basis, enabling Jobs to complete operations and to prioritise operations on behalf of the whole system; a Job assigned with a high budget indicates its priority and value to the manufacturing system. Assuming there are q machines in the system, the set of machines is defined as:

$$M = \{m_1, m_2, \dots, m_q\} \quad (7)$$

The cost for an operation on machine k in budget category j at time t is denoted by $\beta_{kj}(t)$, M_k has capabilities denoted as C_k . MTs operates operational and bidding processes simultaneously, these are governed by the two state charts shown in Figure 5. Figure 5 (a) governs the bidding process, of an initial cost $\beta_{kjn}(t)$, where n is 0, which is a function of the MTs current utilisation and any subsequent rebidding costs, calculated as:

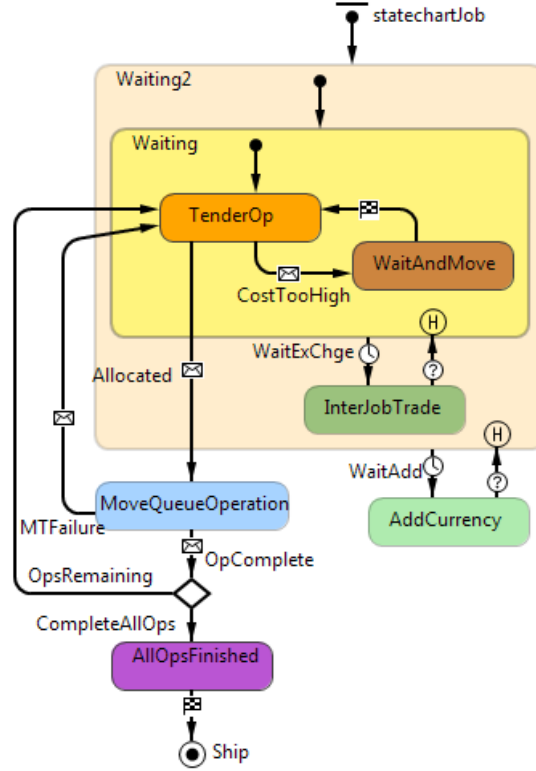


Figure 4. Job agent statechart

$$\beta_{kjn}(t) = 0.8\beta_{max} \cdot \omega_k(t) + 0.2\beta_{max} \quad (8)$$

Where $\omega_k(t)$ is utilisation of MT k at time t and β_{max} is a predefined maximum MT cost. The MT's cost is lowered between bid rounds by $\sigma_{kj}(t)$, which is a function of recent bid success at time t , and defined by:

$$\sigma_{kj}(t) = \sigma_{max}(1 - \tau_k(t)) \quad (9)$$

Where $\tau_k(t)$ is recent bid success of MT k at time t . MT costs for the second and all subsequent bid rounds, $n + 1$, is calculated as:

$$\beta_{kjn+1}(t) = \beta_{kjn}(t) - \sigma_{kj}(t) \quad (10)$$

All functions used in the anarchic manufacturing model are directionally correct, providing a pragmatic and functional device reflecting the free market analogy; the optimised function construction and parameter selection are beyond the necessities of this study. Figure 5 (b) models the MTs operational status, which includes the possibility of failure.

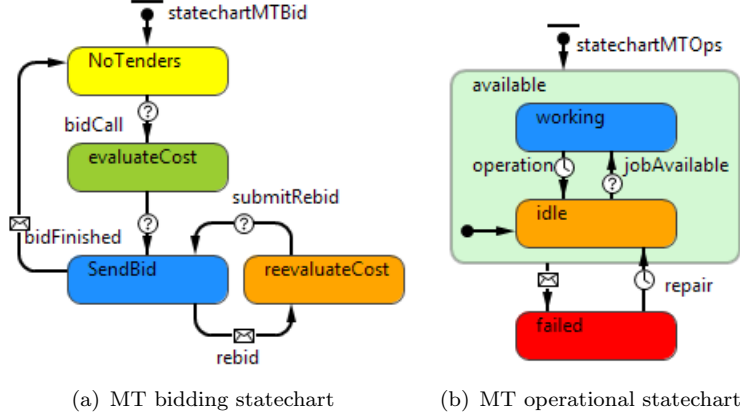


Figure 5. MT agent statechart

3.4. Operation handler agent

There are two purposes for the Operation handler agent: (i) combat asynchronous communication issues associated with agent based modelling, by synchronising communication; and (ii) prioritise messages in a limited communication bandwidth. The single Operation handler agent facilitates the bidding process on behalf of Jobs; ensuring bids are correctly evaluated and each bid round and operation tender is reset accordingly. In practice there are several potential solutions (including timecodes, electronic kanbans) to ensure the execution order in a distributed manner without the use of an Operation handler agent.

4. Negotiation framework

The negotiation framework follows a free market architecture for distributed systems (Dias and Stentz 2000), with local information methods (Scholz-Reiter, Rekersbrink, and G6rges 2010); low level negotiation mechanisms are a combination and adaptation of the contract net protocol with cost factor adaptation (K6d6r and Monostori 2001). There is no predefined structure or objective to maximise flexibility; resources (machine and human) and jobs (materials evolving to products) interact locally to achieve personal goals. This whole distributed scheduling framework is underpinned by the concept of emergent synthesis, where individual agents pursue personal objectives to globally solve unclear problems (Ueda et al. 2001).

Local negotiation mechanisms use a bidding format where a Job invites MTs to tender that are within its communication radius, ϕ_i , and capable of fulfilling its operation tendered, of capability C_i . Initially a Job is prepared to pay a preset fraction of its budget, $\lambda_{ij}(t)$, and calculates an initial threshold below this to try to gain market surplus, $\alpha_{ijn}(t)$ is the Job's threshold bids are evaluated against. MTs fluctuate their cost $\beta_{kjn}(t)$ according to their utilisation, $\omega_k(t)$; this is a permutation of K6d6r's negotiation method (K6d6r and Monostori 2001). If the lowest cost MT β_{jnmin} is below the Job's cost threshold, $\alpha_{ijn}(t)$, the Job is assigned to the MT, if not a second round of bidding is started.

For the second and all subsequent rounds of bidding the Job and MTs reconsider their bids, Jobs increase their cost threshold, by the Job's risk factor $\rho_i(t)$, and MTs lower their cost by an amount they are willing to concede $\sigma_{kj}(t)$, according to its bid

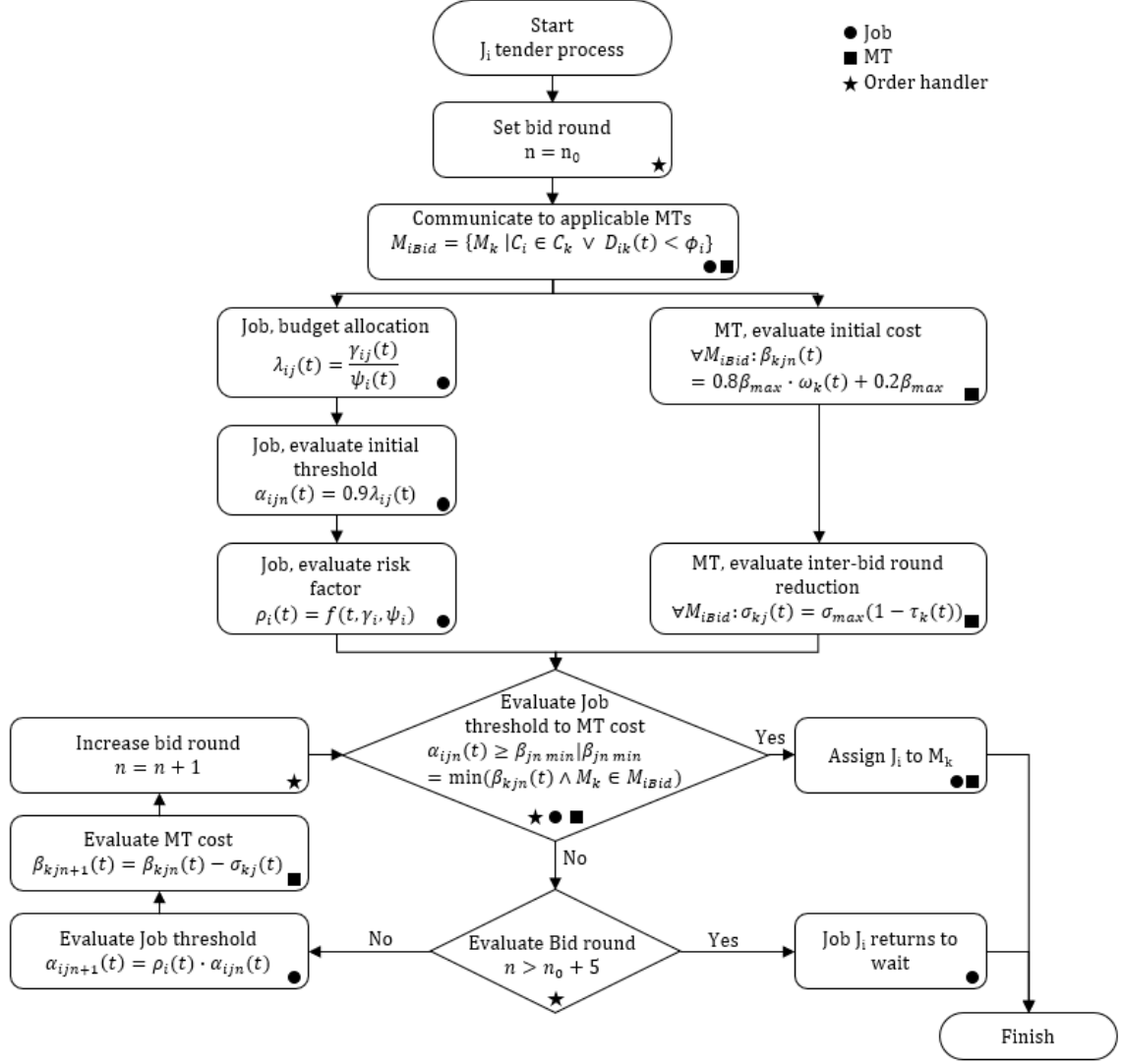


Figure 6. Negotiation process

success, $\tau_k(t)$; this mechanism maximises profits for both agent types but still allocates operations. The rebidding mechanism is repeated for a certain number of rounds, and if unsuccessful the Job gives up and moves elsewhere to restart the tendering process with other MTs. Figure 6 shows the negotiation framework through a flowchart where n is the bid round, α the Job cost threshold, ρ a risk factor that changes over time, γ the overall budget, λ the operation budget ψ number of operations remaining, ϕ the Job's communication range, D the distance between a Job and MT, C the capability of a Job's operation of the MT's capabilities, β the MT cost, σ the MT cost reduction and MT utilisation and bid success are ω and τ respectively. Subscript notation is i the Job number, k the MT number, j the budget currency and n the bid round.

4.1. Multiple currencies

Currency is a familiar but complex concept we all use daily; a currency represents the availability of any or all scarce resources. This scarcity is valued and communicated

through a common and universal medium of currency which is a low-bandwidth mechanism (Dias and Stentz 2000). This in turn will value each goods and services in the society relative to the society's current needs, here the agents within the manufacturing environment makeup the society.

Three different currencies were modelled, to represent multiple aspects or priorities that a real manufacturer may face. Accounting for monetary cost, CO2 emissions or other environmental stipulations; modelled as operational, emissions and environmental currency respectively. This contributes to the free market paradigm, and addresses and weights multiple objectives that a hierarchical system or a rule-based distributed system cannot.

4.2. *Inter-job trading*

Exchange of multiple currencies is a device borrowed from economics, where trading revalues a currency's relative worth through dynamic exchange rates (Zimmermann, Neuneier, and Grothmann 2001). Within the anarchic manufacturing system, if a Job has been unable to complete its next operation, due to a budget deficit with one or multiple different currencies, it will communicate with nearby Jobs and assess whether it can trade one currency for another. Jobs are subjected to a trade if they have a relative surplus of one currency over another, therefore the trade does not detriment another Job. This trade is at a predefined exchange rate for modelling simplicity; at an approximate average operation cost for each relevant currency. The inter-job trading mechanism is used to share and reallocate resources within the society efficiently, as a passive collaborative mechanism between homogeneous agents still preserving their competitive nature.

5. Hierarchical framework

A simple hierarchical manufacturing system was used to compare the relative performance to distributed systems. An instantaneous FIFO system was used to allocate the Jobs to the next available MT for the next operation only, in order that they reported to the centralised scheduling agent. Rescheduling is triggered to redistribute jobs, that are queuing and not being operated on, to MTs when a disruptive event occurs (i.e. MT failure) or when the distribution of work is notably imbalanced (i.e. an idle MT whilst there are jobs waiting, more than a preset number of jobs waiting for scheduling). It is assumed there is perfect system knowledge, and rescheduling is triggered and completed instantaneously; any time delay would be arbitrary and was therefore not modelled. The differing levels of system sophistication is not relevant, as the relative performance as a parameter increases is analysed.

6. Experimental framework

The framework is implemented on the AnyLogic modelling platform, a multi-method simulation environment. Two sets of experiments were conducted, the first to measure performance against Taillard's benchmark problems which are a known standard (Taillard 1993), the second to characterise relative flexibility against an hierarchical system by subjecting the systems to unforeseen disruption.

6.1. Taillard's benchmark problems

Taillard's benchmark problems were used to compare the anarchic and simple hierarchical (FIFO) systems against standardised job shop problems, measuring total makespan (Taillard 1993). The anarchic framework, described above, was modified for Taillard's problems, as these are static scenarios with a single objective to minimise makespan multiple currencies are not appropriate. A single currency was used and the initial bid, β_0 , from MTs was calculated as:

$$\beta_0 = \frac{\omega}{2} + \frac{k}{2} \quad (11)$$

where ω is MTs utilisation and k is the duration of the operation considered. The cost factor reduction, σ , was modified to:

$$\sigma = \frac{2}{\nu} + 1 \quad (12)$$

where ν is the historical success rate of the MT's bidding process. ϕ is chosen as 15m in the model space, corresponding to 25% communication coverage for agents.

Four job shop scenarios were run from Taillard's benchmark problems; 15 Jobs and 15 MTs, 20 Jobs and 15 MTs, 50 Jobs and 20 MTs and 50 Jobs and 15 MTs. The overall makespan was recorded for both the anarchic and hierarchical systems.

6.2. Job shop flexibility testing

Flexibility experiments were created to understand performance under dynamic environments, emulating real-world disruptions, testing against temporal and range dimensions of flexibility (Golden and Powell 2000). The modelled manufacturing systems was subjected to unforeseen disruption, Key Performance Indicators (KPI) were recorded and compared. Experiments followed Taguchi's design of experiments, to efficiently compare a high number of interacting parameters (Clemson et al. 1995).

Key Performance Indicators

Key performance indicators were selected to reflect the qualitative definition of flexibility in Section 2.4. Throughput measures efficiency and overall performance, the standard deviation of throughput measures the responsiveness of the system to stabilise after disruption. Time in system (TIS) indicates Work In Progress (WIP) levels, and categorises the system's lean and level of job delays indicating responsiveness. Robustness is not directly measured, however, it is inferred qualitatively from all metrics; there is currently insufficient knowledge and lack of clarity as what defines robustness (Golden and Powell 2000).

System layout

For experimentation a simple scalable job shop layout was selected with 12 Machines with capabilities A and/or B that an operation requires, were laid out in a uniform pattern for scalability. When Jobs are created they search for a machine in the central blue box, and on completing all necessary operations exit the system at the 'Ship' point.

Table 1. Parameter levels for flexibility testing

No.	Parameter	Level 1	Level 2	Level 3
1	Speed of movement	3 ms ⁻¹	10 ms ⁻¹	Not used
2	Job arrival rate, increased from 10 min ⁻¹ (% theoretical stability without MT failure)	12 min ⁻¹ (58%)	14 min ⁻¹ (68%)	18 min ⁻¹ (88%)
3	MT failure rate, % total capacity	6.7%	20.0%	33.3%
4	Randomness of operation length % range of average operation duration	±6%	±30%	±57%
5	Number of MTs (% capacity increase on level 1)	12 MTs	13 MTs (8%)	15 MTs (25%)
6	Environmental budget allocation for jobs per operation	35	50	100
7	Randomness of budget allocation	0%	±10%	±30%
8	Communication range, metres (% complete coverage)	15m (26%)	20m (34%)	50m (86%)

Parameters and Taguchi method

Parameter and scenario selection were based on real world scenarios and varying system capability. Certain scenarios and parameters were excluded due to: model limitations, their effect on the clarity of results and parameter prioritisation. The Taguchi method was followed, to significantly reduce the number of experiments whilst testing a high number of variables (Clemson et al. 1995).

The parameters, and their varying levels for Taguchi experiments following L18 orthogonal arrays, are shown in Table 1. Note that parameters 6-8 only impact the anarchic system and have no impact on the hierarchical system. Each experiment was run six times, using randomly generated numbers as inputs for relevant parameters with variability, parallel experiments between hierarchical and anarchic systems used identical random number inputs.

7. Results

7.1. Taillard’s benchmark problems

The results for the four Taillard’s job shop problems, reporting the anarchic and FIFO makespan against Taillard’s published lower bounds (Taillard 1993), indicate that the anarchic system achieves a makespan approximately 6% shorter than the hierarchical FIFO system, but 25% longer than the lower bound establish by Taillard.

These job shop problems are static with fixed processing times and exclude variables such as set-up times, due dates, or release dates. These scenarios have limitations emulating the real world where dynamic environments including variability and disruptions occur. However, they do validate the performance of both systems as comparable and of reasonable capability when compared to Taillard’s published lower bound (Taillard 1993).

7.2. Job shop flexibility tests

The raw data for average throughput and average time in system metrics have significant noise, therefore a rolling average was used to read the results. All metrics were measured during the disruption period; for standard deviation of the throughput, absolute measurements were taken against the average throughput.

All three KPIs measured have a lower the better value. To compare the two systems, the KPI for each was normalised to a percentage performance level, these two were directly compared by subtracting the hierarchical from anarchic performance.

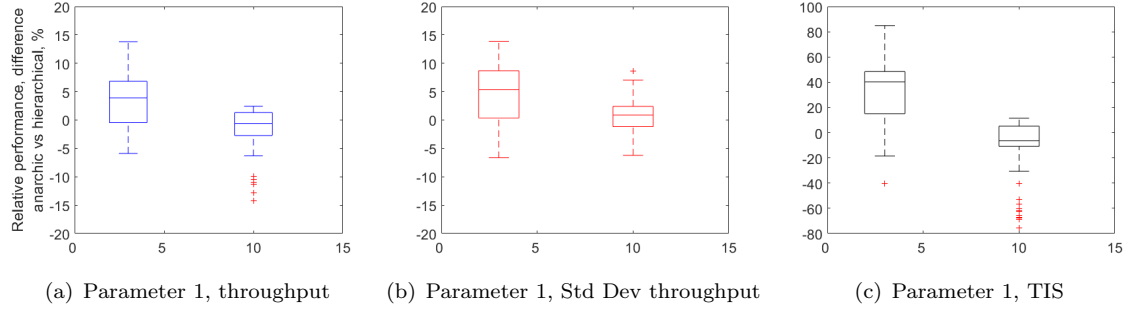


Figure 7. Parameter 1 Job speed

A positive result indicates the anarchic system performed relatively better than the hierarchical, this data analysis method was used for all results in Figures 7-14. As the trend of relative performance as a parameter increases was analysed, the absolute performance is not relevant to the analysis or relative characterisation of flexibility.

Following the Taguchi method (Clemson et al. 1995), in Figures 7-14 are the parameter levels plotted the anarchic performance against hierarchical, the parameter level has been normalised where possible. The relative performance (Y-axis) is compared to an increasing parameter level (X-axis), therefore a positive trend line / gradient indicates a relatively better anarchic performance as the parameter level increases. This comparative method negates the difference in absolute performance, by measuring the relative change as a parameter increases.

Parameters are grouped to test the systems for unforeseen disruption and overall system performance. The unforeseen disruption parameters' 2-4 results displayed in Figures 8-10, indicate level of system robustness. From all metrics there are no distinct trends, indicating that there is no clear relative improvement in performance as disruption increases. Parameters testing system performance were largely associated with the free market paradigm the anarchic system was designed to. Parameters 1 and 5-8 evaluate how the anarchic system deals with different environment conditions, aiming to display any emergent free market traits. Parameter 1, job speed, shows the hierarchical system's reliance on speed of movement; as Figure 7 shows a decreasing relative anarchic performance as speed increases. Parameter 5, additional MT capacity displayed in Figure 11, shows a flat trend line indicating both are as capable to utilise an increase in MT capacity. Parameter 6, environment budget, shows there is a peak allocation where the free market and multiple currency mechanisms work optimally. Parameter 7, randomness of budget allocation, shows how the anarchic system can effectively reallocate resources as there is no clear degradation in performance as randomness increases. Parameter 8, communication range, from Figure 14 shows a clear improvement in performance as communication increases; thereby increasing both performance and range of inter-job trading, both support the free market paradigm.

8. Discussion

8.1. Characterisation of flexibility

The anarchic system has not been shown to be more flexible than the hierarchical system under increasing levels of unforeseen disruption. Increasing parameters 2, 3, 4 (job arrival rate, MT downtime, randomness of operation duration) relative performance

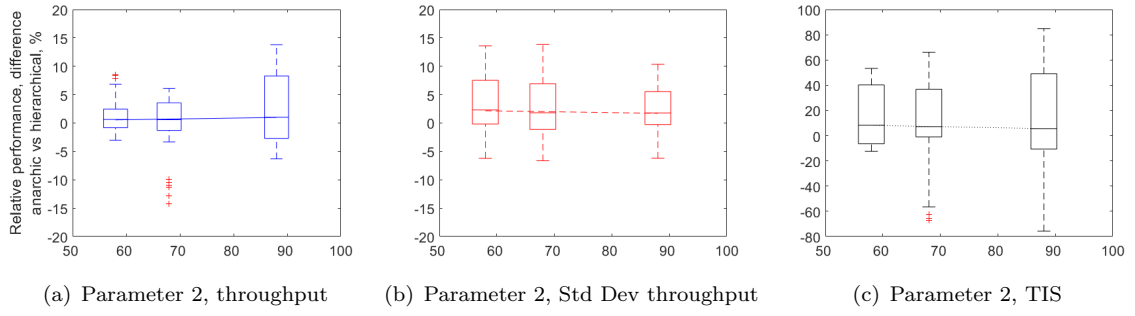


Figure 8. Parameter 2 Job arrival rate

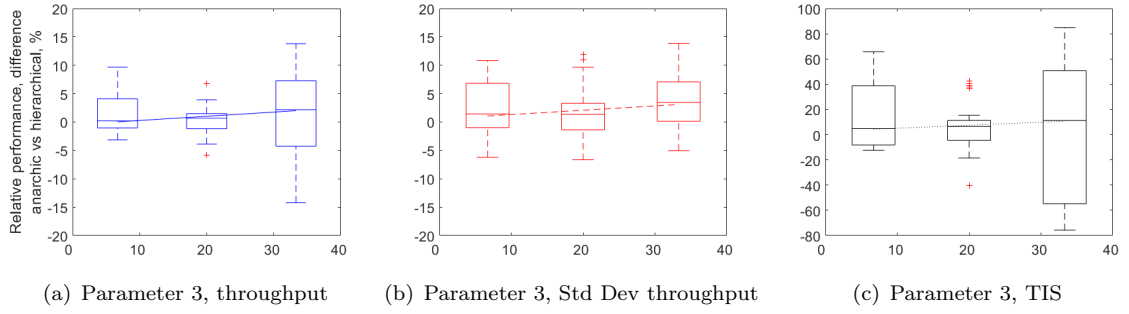


Figure 9. Parameter 3 MT failure

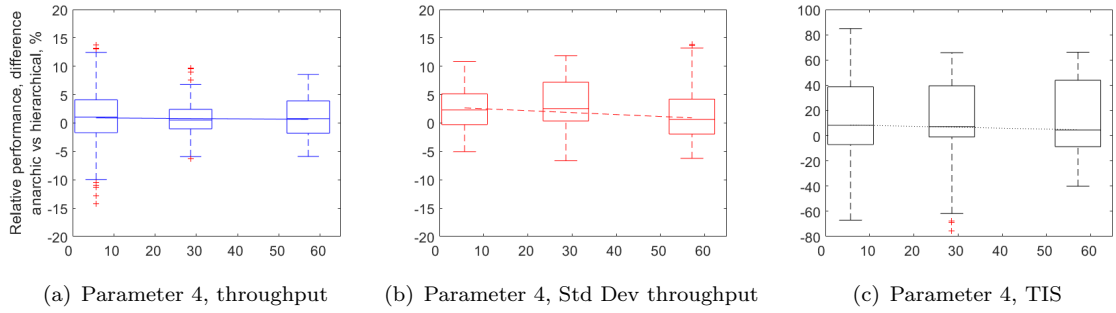


Figure 10. Parameter 4 Randomness operation length

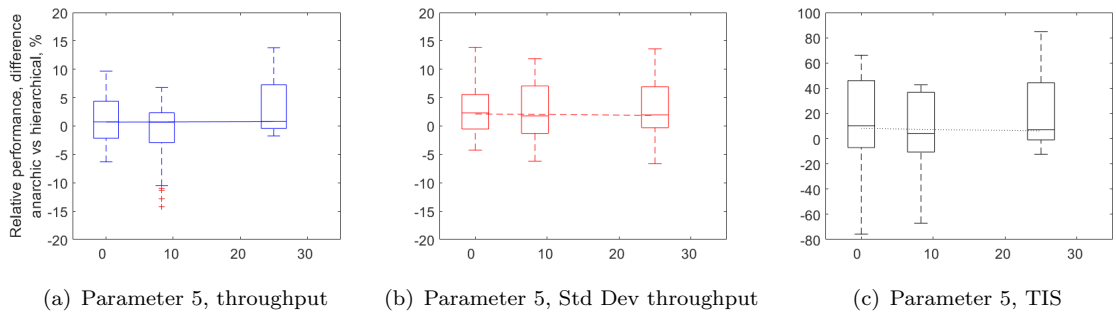


Figure 11. Parameter 5 additional MT capacity

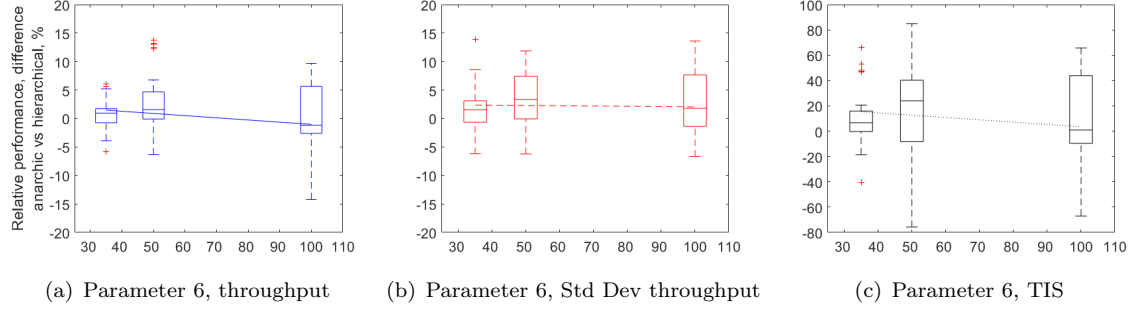


Figure 12. Parameter 6 Environment budget

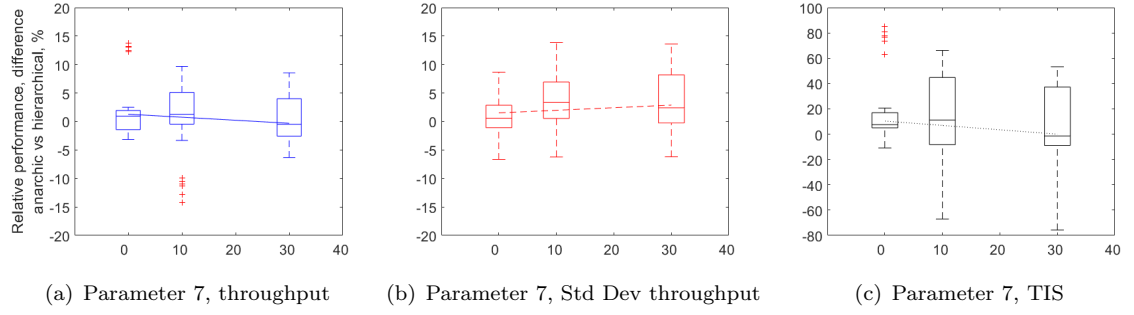


Figure 13. Parameter 7 Randomness budget allocation

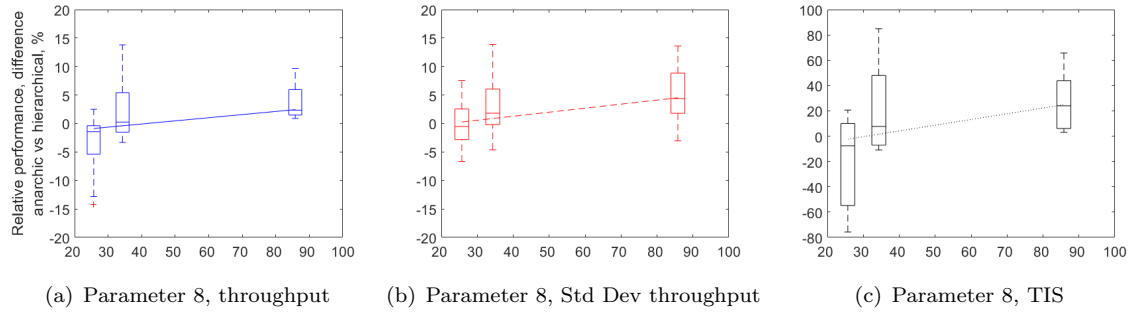


Figure 14. Parameter 8 Communication range

remained the same, indicating that the anarchic system is as robust as the hierarchical system. The anarchic system did perform relatively better against parameter 4 (randomness of operation duration), however, the increase was too small to suggest greater flexibility.

In comparison to other similar studies, Windt, Böse, and Philipp (2008) use a rule-based decision making autonomous control system in a job shop scenario, and concludes a centralised system leads to suboptimal performance whereas increasing autonomy improves overall performance against logistics objectives. They suggest that peak performance is achieved against a certain level of autonomy, and that fully decentralised systems similar to the anarchic system are not optimal due to chaotic behaviour. Chaotic behaviour was not observed in this study, however the conclusion that the anarchic system was not shown to be more flexible than hierarchical system cannot be compared to Windt, Böse, and Philipp’s paper. Additionally, this investigation contradicts the common preconception that distributed systems are more flexible than hierarchical ones (Cantamessa 1997; Scholz-Reiter, Rekersbrink, and Görges 2010; Rekersbrink, Makuschewitz, and Scholz-Reiter 2009; Ouelhadj and Petrovic 2009; Rahimifard and Newman 2001).

The results may be due to a relatively efficient hierarchical system, using a dynamic heuristic and operating in an idealised state with instantaneous triggered rescheduling; as soon as the system is operating in a suboptimal state. The anarchic system has been shown to be as adaptable and efficient to this rapidly responding hierarchical system.

8.2. *Self-optimising and adaptability*

The anarchic system has shown signs of being dynamically self-optimising and adapting to volatility, without the need for complete information; supporting Cantamessa’s claim that agent-based models are workload levelling (Cantamessa 1997). This is largely drawn from inter-job trading of different currencies, thereby sharing the available resources within the job agent society. This is done without penalising individual jobs that have been prioritised through increased budget allocation.

This dynamic self-optimisation has been shown in results for parameters 6 and 7 (environment budget allocation, randomness of budget allocation). As exchange rates are fixed and are not dynamic, an insufficient or excessive allocation of one currency budget will be suboptimal and impede the inter-job trading mechanism. This has been shown in parameter 6, where performance peaks at an optimal budget allocation for each job and the agent society. Suboptimal budget allocations significantly impede the inter-job trading mechanism and subsequent performance. Concurrently the consistency in performance against parameter 7 (budget allocation randomness) which only impacts the anarchic system, indicates that the anarchic system can redistribute currency appropriately between jobs to overcome volatility, achieving a consistent global performance.

The anarchic system does not need complete information at any single point in the system, rather the centralised system does; this can provide an advantageous system for naturally distributed scenarios. Ueda states that centralised systems and top-down analytics is being replaced by bottom-up synthesis, and that distributed emergent synthetic methods are best to deal with unclear problems for both requirements specification and the environment (Ueda, Lengyel, and Hatono 2004). The anarchic system has been shown to perform comparatively well to a centralised system in Taillard’s benchmark problems, but unlike a centralised system it does not require full system

knowledge at any single point.

8.3. *Free market attributes*

The anarchic system was created to emulate a free market architecture for distributed systems (Dias and Stentz 2000) using a low level variant of the contract net protocol with cost factor adaptation (Kádár and Monostori 2001). These attributes are evident in parameter 6 and 8 (environmental budget allocation, communication distance) as optimal currency allocation and system knowledge increases, the anarchic system improves; these parameters do not impact the hierarchical system.

Increasing parameter 8, the Jobs' communication range, improves the transfer of information; thereby increasing competition between MTs for Job operations and efficiency of reallocating currency through the inter-job trading mechanism. The significant improvement, from increasing communication range and system knowledges, demonstrates free market attributes as overall performance improves as the multi agent society tends towards perfect knowledge. This suggests the free market based anarchic platform is capable of further development, for example using economics game theory.

8.4. *Limitations*

Experimental results have been limited from a number of factors, including; stochasticity of non-deterministic agent based modelling, free market mechanisms and the Taguchi method. Stochasticity within simulation modelling is an inherent feature of agent based modelling, which enables emergent behaviour but also provides a range of results. Basic free market mechanisms were selected to create directional behaviour, game theory improvements require further investigation. The Taguchi method was selected as an exploratory methodology approach to test many parameters efficiently (Clemson et al. 1995), however, the most sensitive parameters created noise.

9. *Conclusions*

The anarchic system was shown to be as robust and flexible as the simple hierarchical system under unforeseen disruption. There is no clear relative inherent flexibility displayed, this may be due to the simulation model operating in an idealised state; with instantaneous communication and processing. The distributed anarchic system has, however, demonstrated self-optimising and free market attributes; being able to dynamically self-optimize random budget allocation and improving overall efficiency as the proliferation of knowledge increased.

The distributed anarchic system proposed could have real-world application for smart factories, limited communication bandwidth scenarios and volatile environments. Brettel et al. states that modular decentralised systems will be the future for Industry 4.0 (Brettel et al. 2014). Where smart factories, of highly complex supply chains and products with a dynamically changing product mix, could benefit from autonomous anarchic manufacturing to manage complexity; whilst maintaining a customer-centric approach realised by bottom up decision making. Scenarios and systems with limited communication bandwidth would benefit from a lack of reliance on a centralised communication and infrastructure. An anarchic solution may be suited for volatile environments with critical operations, reducing the dependability

on infrastructure and communications; using the anarchic system’s adaptability and self-optimising traits displayed in this paper. Future work will evaluate and compare a hierarchical and anarchic system as complicatedness and complexity increases; which are key challenges envisaged for Industry 4.0. For example, increasing the number of different shared and non-coupled resources required to complete an operation increases complexity.

References

- Allwood, Julian M., Tom H.C. Childs, Adam T. Clare, Anjali K.M. De Silva, Vimal Dhokia, Ian M. Hutchings, Richard K. Leach, et al. 2015. “Manufacturing at double the speed.” *Journal of Materials Processing Technology* 229: 729–757.
- Berglund, M., and J. Karlton. 2007. “Human, technological and organizational aspects influencing the production scheduling process.” *International Journal of Production Economics* 110 (1-2): 160–174.
- Bi, Z. M., S. Y. T. Lang, W. Shen, and L. Wang. 2008. “Reconfigurable manufacturing systems: the state of the art.” *International Journal of Production Research* 46 (4): 967–992.
- Bigus, Joseph, and Jennifer Bigus. 2001. *Constructing intelligent agents using Java*.
- Borshchev, Andrei. 2013. *The Big Book of Simulation Modelling: Multimethod Modelling with AnyLogic 6*.
- Brettel, Malte, Niklas Friederichsen, Michael Keller, and Marius Rosenberg. 2014. “How Virtualization, Decentralization and Network Building Change the Manufacturing Landscape: An Industry 4.0 Perspective.” *International Journal of Mechanical, Aerospace, Industrial, Mechatronic and Manufacturing Engineering* 8 (1): 37–44.
- Cantamessa, M. 1997. “Agent-based modeling and management of manufacturing systems.” *Computers in Industry* 34 (97): 173–186.
- Chang, F. C.R. 1997. “Heuristics for dynamic job shop scheduling with real-time updated queueing time estimates.” *International Journal of Production Research* 35 (3): 651–665.
- Clemson, Barry, Yongming Tang, James Pyne, and Resit Unal. 1995. “Efficient methods for sensitivity analysis.” *System Dynamics Review* 11 (1): 31–49.
- Dias, M Bernardine, and Anthony Stentz. 2000. “A Free Market Architecture for Distributed Control of a Multirobot System.” *6th International Conference on Intelligent Autonomous Systems IAS6* 6: 115–122.
- Golden, William, and Philip Powell. 2000. “Towards a definition of flexibility: In search of the holy grail?” *Omega* 28 (4): 373–384.
- Heragu, Sunderesh S, Robert J Graves, Byung-in Kim, and Art St Onge. 2002. “Intelligent Agent Based Framework for Manufacturing Systems Control.” *IEEE Trans. Syst. Man. Cybern.* 32 (5): 560–573.
- Hosseinabadi, Ali Asghar Rahmani, Hajar Siar, Shahaboddin Shamshirband, Mohammad Shojafar, and Mohd Hairul Nizam Md. Nasir. 2015. “Using the gravitational emulation local search algorithm to solve the multi-objective flexible dynamic job shop scheduling problem in Small and Medium Enterprises.” *Annals of Operations Research* 229 (1): 451–474.
- Hu, S. Jack. 2013. “Evolving paradigms of manufacturing: From mass production to mass customization and personalization.” *Procedia CIRP* 7: 3–8.
- Hülsmann, Michael, and Katja Windt. 2007. *The Impact of Autonomy on Management, Information, Communication and Material Flow*. Springer.
- Ivanov, Dmitry, Ajay Das, and Tsan Ming Choi. 2018. “New flexibility drivers for manufacturing, supply chain and service operations.” *International Journal of Production Research* 56 (10): 3359–3368.
- Jovane, F., Y. Koren, and C.R. Boer. 2003. “Present and Future of Flexible Automation: Towards New paradigms.” *Annals of the CIRP* 52/2 (1): 543–557.
- Kádár, Botond, and László Monostori. 2001. “Approaches to Increase the Performance of

- Agent-Based Production Systems.” 612–621.
- Koren, Y., U. Heisel, F. Jovane, T. Moriwaki, G. Pritschow, G. Ulsoy, and H. Van Brussel. 1999. “Reconfigurable Manufacturing Systems.” *CIRP Annals* 48 (2): 527–540.
- Koren, Yoram, Wencai Wang, and Xi Gu. 2017. “Value creation through design for scalability of reconfigurable manufacturing systems.” *International Journal of Production Research* 55 (5): 1227–1242.
- Kusiak, Andrew. 2018. “Smart manufacturing.” *International Journal of Production Research* 56 (1-2): 508–517.
- Liu, Yongkui, Lihui Wang, Xi Vincent Wang, Xun Xu, and Lin Zhang. 2018. “Scheduling in cloud manufacturing: state-of-the-art and research challenges.” *International Journal of Production Research* 7543: 1–26.
- Mehrabi, M. G., A. G. Ulsoy, and Y. Koren. 2000. “Reconfigurable manufacturing systems: key to future manufacturing.” *Journal of Intelligent Manufacturing* 11 (4): 403–419.
- Meissner, Hermann, Rebecca Ilse, and Jan C. Aurich. 2017. “Analysis of Control Architectures in the Context of Industry 4.0.” *Procedia CIRP* 62: 165–169.
- Mourtzis, D., and M. Doukas. 2014. “Design and planning of manufacturing networks for mass customisation and personalisation: Challenges and outlook.” *Procedia CIRP* 19 (C): 1–13.
- Narasimhan, Ram, Srinivas Talluri, and Ajay Das. 2004. “Exploring flexibility and execution competencies of manufacturing firms.” *Journal of Operations Management* 22 (1): 91–106.
- Nassehi, Aydin, and Andrew Ma. 2017. “A Prelude to Anarchic Manufacturing Systems.” In *7th International Conference on Industrial Engineering and Systems Management*, .
- Ouelhadj, Djamil, and Sanja Petrovic. 2009. “A survey of dynamic scheduling in manufacturing systems.” *Journal of Scheduling* 12 (4): 417–431.
- Pendharkar, Parag C. 2012. “Game theoretical applications for multi-agent systems.” *Expert Systems with Applications* 39 (1): 273–279.
- Pendharkar, P.C. 1999. “A computational study on design and performance issues of multi-agent intelligent systems for dynamic scheduling environments.” *Expert Systems with Applications* 16 (2): 121–133.
- Rahimifard, S, and S T Newman. 2001. “The planning and control of manufacturing SMEs.” ... *Journal of Manufacturing Technology and ...* 1–16.
- Rekersbrink, Henning, Thomas Makuschewitz, and Bernd Scholz-Reiter. 2009. “A distributed routing concept for vehicle routing problems.” *Logistics Research* 1 (1): 45–52.
- Ryu, Kwangyeol, and Mooyoung Jung. 2003. “Agent-based fractal architecture and modelling for developing distributed manufacturing systems.” *International Journal of Production Research* 41 (17): 4233–4255.
- Scholz-Reiter, B., and M. Freitag. 2007. “Autonomous Processes in Assembly Systems.” *CIRP Annals - Manufacturing Technology* 56 (2): 712–729.
- Scholz-Reiter, B., H. Rekersbrink, and M. Görges. 2010. “Dynamic flexible flow shop problems - Scheduling heuristics vs. autonomous control.” *CIRP Annals - Manufacturing Technology* 59 (1): 465–468.
- Scholz-Reiter, B., K. Windt, and M. Freitag. 2004. “Autonomous Logistic Processes: New Demands and First Approaches.” *Proc. 37th CIRP International Seminar on Manufacturing Systems* (2): 357–362.
- Sethi, Andrea Krasa, and Suresh Pal Sethi. 1990. “Flexibility in manufacturing: A survey.” *International Journal of Flexible Manufacturing Systems* 2 (4): 289–328.
- Shamshirband, Shahaboddin, Mohammad Shojafar, A. A.Rahmani Hosseinabadi, Maryam Kardgar, M. H.N.Md Nasir, and Rodina Ahmad. 2015. “OSGA: Genetic-based open-shop scheduling with consideration of machine maintenance in small and medium enterprises.” *Annals of Operations Research* 229 (1): 743–758.
- Shen, Weiming, Qi Hao, Hyun Joong Yoon, and Douglas H. Norrie. 2006. “Applications of agent-based systems in intelligent manufacturing: An updated review.” *Advanced Engineering Informatics* 20 (4): 415–431.
- Shen, Weiming, and Douglas H. Norrie. 1999. “Agent-Based Systems for Intelligent Manufacturing: A State-of-the-Art Survey.” *Knowledge and Information Systems* 1 (2): 129–156.

- Shen, Weiming, Maturana, Francisco & Norrie, Douglas H. 2000. "MetaMorph II : an agent-based architecture for distributed intelligent design and manufacturing." *Journal of Intelligent Manufacturing* 11: 237–251.
- Taillard, E. 1993. "Benchmarks for basic scheduling problems." *European Journal of Operational Research* 64: 278–285.
- Ueda, K., N. Fujii, and R. Inoue. 2007. "An Emergent Synthesis Approach to Simultaneous Process Planning and Scheduling." *CIRP Annals - Manufacturing Technology* 56 (1): 463–466.
- Ueda, K., T. Kito, and N. Fujii. 2006. "Modeling biological manufacturing systems with bounded-rational agents." *CIRP Annals - Manufacturing Technology* 55 (1): 469–472.
- Ueda, K., A. Lengyel, and I. Hatono. 2004. "Emergent synthesis approaches to control and planning in make to order manufacturing environments." *CIRP Annals - Manufacturing Technology* 53 (1): 385–388.
- Ueda, K., A. Markus, L. Monostori, H. J.J. Kals, and T. Arai. 2001. "Emergent synthesis methodologies for manufacturing." *CIRP Annals - Manufacturing Technology* 50 (2): 535–551.
- Ueda, Kanji, Jari Vaario, and Kazuhiro Ohkura. 1997. "Modelling of Biological Manufacturing Systems for Dynamic Reconfiguration." *CIRP Annals - Manufacturing Technology* 46 (1): 343–346.
- Windt, Katja, Felix Böse, and Thorsten Philipp. 2008. "Autonomy in production logistics: Identification, characterisation and application." *Robotics and Computer-Integrated Manufacturing* 24 (4): 572–578.
- Wooldridge, Michael, Chester Street, M Manchester, and Nicholas R Jennings. 1995. "Intelligent Agents : Theory and Practice." 10 (October 1994): 1–62.
- Wu, Dazhong, Matthew John Greer, David W. Rosen, and Dirk Schaefer. 2013. "Cloud manufacturing: Strategic vision and state-of-the-art." *Journal of Manufacturing Systems* 32 (4): 564–579.
- Zimmermann, H. G., R. Neuneier, and R. Grothmann. 2001. "Multiagent modeling of multiple FX-markets by neural networks." *IEEE Transactions on Neural Networks* 12 (4): 735–743.